THE EFFECTS OF CLIMATIC VARIABILITY ON US IRRIGATION ADOPTION

DONALD H. NEGRI[1], NOEL R. GOLLEHON[2] and MARCEL P. AILLERY[3]

[1]*Department of Economics, Willamette University, 900 State Street, Salem, Oregon 97301, U.S.A.*
E-mail: dnegri@willamette.edu
[2]*Economic Research Service, 1800 M Street NW, Room 4047, Washington, DC 20036-5831, U.S.A*
[3]*Economic Research Service, 1800 M Street NW, Room 4011, Washington, DC 20036-5831, U.S.A*

Abstract. This paper contributes to the literature underscoring the importance of climatic variance by developing a framework for incorporating the means and tails of the distributions of rainfall and temperature into empirical models of agricultural production. The methodology is applied to estimate the impact of climate change on the discrete choice decision to adopt irrigation since it is an important adaptation to climate change. We develop a discrete choice model for the decision to install irrigation capacity that captures the effects of both climate means and extremes. Climatic means and frequencies of climatic events in the upper tails of the temperature and precipitation distributions are used to estimate the parameters of a normal distribution for temperature and a Weibull distribution for precipitation. Using estimates from a probit model, we examine the independent effects of changing climatic mean and variance on the probability of adopting irrigation. Increasing the mean temperature, holding variance constant, shifts the entire distribution toward warmer temperatures – increasing the frequency of extreme temperatures. For precipitation, the specification captures the separate effects of mean rainfall, frequency of rainfall, and frequency of extreme events. The results show that the tails of the temperature and precipitation distributions, not the means, are the dominant climatic determinants in irrigation adoption. The results also show that water availability, soil characteristics, farm size and operator demographics are important determinants of irrigation.

1. Introduction

The prospect of global warming over the next century has prompted numerous studies of the impacts of warmer climate on US agriculture. The consensus in the literature is that the adverse impacts of global warming on aggregate US agriculture are likely to be small, although regional impacts may be significant (see Kaiser Crosson, 1995; and Lewandrowski and Schimmelpfennig, 1999, for surveys). Indeed, several studies (e.g., Mendelsohn, et al., 1994) predict a net economic benefit. Until recently, however, many of these studies shared a common deficiency: they did not adequately account for changes in the frequency or magnitude of extreme climatic events such as excessive heat or cold, torrential rain, or prolonged drought. The methods in these studies implicitly or explicitly assumed that the first moment of the climate probability distributions would capture the agricultural impact of climate change. Extreme events, which can be summarized by higher order moments of the distribution, were largely ignored.

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Global climate change will almost certainly affect more than the first moments of the precipitation and temperature distributions. Even holding variance constant, an increase in mean temperature will increase the frequency and severity of hot days as the entire distribution shifts toward higher temperatures. Similarly, climate change will alter the frequency, intensity, and duration of precipitation events. Statistics which summarize only the first moment of these distributions cannot adequately capture the impact of changes in the probability of events in the tails of the distributions because the relationship between means and extremes tends to be nonlinear. Moreover, relatively small changes in variance can lead to a disproportionately large increase in the frequency and severity of extreme events because extremes of temperature and precipitation are more sensitive to changes in variance than changes in the mean (Katz and Brown, 1992).

Several recent studies explicitly address the impact of climate variability on agriculture and establish that climate variability is a significant determinant of agricultural land value (Mendelsohn et al., 1999), yields (Mearns et al., 1996), profits (Dixon and Segerson, 1999), and consumer and producer welfare (Dalton, 1997).[1]

This paper contributes to the literature underscoring the importance of climate variance by developing a framework for incorporating climatic variance and extreme events into an empirical model of irrigation adoption. Using readily available climatic data, we estimate a probit model that captures the effects of both climate means and extremes on the decision to adopt irrigation. Information about producer adaptation to the distribution of temperature and precipitation, including the risk of extreme events, is embodied in prevailing agricultural practices. An empirical model based on a geographic cross-section that includes variables that proxy for extreme events can estimate on-farm adaptations to changing climatic conditions. The methodology is applied to the decision to adopt irrigation; however, it can be applied more generally to empirically analyze other agricultural impacts of climate change.

The relationship between agricultural production and the biophysical conditions within which it occurs is extremely complex. Indeed, many dimensions of climate affect agriculture, with complex interactions among climatic variables themselves and across other biophysical conditions such as soil structure. This research, while not completely unraveling these complex relationships, establishes, separate and distinct from measures of climate mean, the importance of climate variance and extreme events in the decision to adopt irrigation.

Section 2 develops a discrete choice model of agricultural production that permits input and output substitution. In this framework, the probability of adopting irrigation is estimated as a function of input and output prices, farm size, and a vector of exogenous physical conditions including climate. Section 3 describes the farm-level, geo-referenced data and independent variables developed to estimate a probit model of the decision to adopt irrigation. The explanatory variables include measures of the tails of the temperature and precipitation distributions and interaction terms among selected biophysical conditions. The parameter estimates are reported and discussed in Section 4. Section 5 parameterizes the temperature and precipitation distributions and, using estimates from the probit model, simulates the independent effects of climatic mean and variance on the probability of adopting irrigation. Section 6 summarizes our results and suggests productive avenues for future research.

2. Model

A multi-output production model can be used to explore the complex influences of climate on agricultural production decisions. The formal model is based on a multi-output production model with land as a fixed, allocatable input (Shumway et al., 1984). A discrete input choice rendering of the multi-output model was developed in Negri and Brooks (1990) and is well suited for this investigation since it permits both output and input substitution and discrete choice of inputs. Altering input and output mix offers important adaptive strategies to climatic change. Producers can adapt by altering production practices and applying inputs that mitigate the risk of adverse climatic events. On the output side, multi-output producers can adapt to exogenous climate conditions by altering the mix of crops.

Briefly summarizing the formal elements of the model, let $\mathbf{Y}$ be a vector of agricultural commodity outputs and $\mathbf{P}$ a vector of exogenous output prices; $\mathbf{X}$ is a vector of variable inputs (e.g., labor, water, fertilizer, energy, etc.) and $\mathbf{W}$ a vector of exogenous input prices. Let T be a scalar representing the discrete choice of irrigation capacity (i.e., on-farm investment in irrigation systems to supplement natural precipitation) and ω, the lump-sum annualized capital cost of irrigation. Let θ be a vector of exogenous physical characteristics including climate and soil conditions that affect inputs and outputs.

In this approach, land is treated as a fixed input in the production of agricultural outputs.[2] Fixed land, profit maximization, competitive input and output markets and well-defined production technology yield a well-defined indirect profit function for the multi-output producer. Let the scalar N denote the quantity of fixed, allocatable land on the farm. Assuming land is fixed and variable inputs are continuous, the multicrop indirect profit function can be written as a function of output and variable input prices and fixed input quantities (Chambers and Just, 1989).

$$\Pi(\mathbf{P}, \mathbf{W}, \omega, N, \boldsymbol{\theta}) = \max_{X,T}\{\mathbf{P'Y} - \mathbf{W'X} - \omega T : Y \in Y(\mathbf{X}, \boldsymbol{\theta}, N, T)\}, \tag{1}$$

where $Y(\mathbf{X}, \boldsymbol{\theta}, N, T)$ is the restricted production possibilities set imposed by the production technology and constraints on land, N, physical characteristics, $\boldsymbol{\theta}$, and discrete irrigation capacity choice, T.

The decision to produce agricultural commodities using irrigation as opposed to farming with natural precipitation only (i.e., dryland) is assumed to be discrete and dichotomous; irrigation capacity is installed or it is not. Let T_{I} and T_{D} denote a production technology using irrigation and dryland production, respectively.

Separate indirect profit functions associated with the discrete choice of irrigation can be written as,

$$\Pi_{\mathrm{I}}(\mathbf{P}, \mathbf{W}, \omega, N, \boldsymbol{\theta}) = \max_{X}\{\mathbf{P'Y} - \mathbf{W'X} - \omega T_{\mathrm{I}}\colon Y \in \mathrm{Y}(\mathbf{X}, \boldsymbol{\theta}, N, T_{\mathrm{I}})\} \text{ (irrigated)}$$

$$\text{and, } \Pi_{\mathrm{D}}(\mathbf{P}, \mathbf{W}, N, \boldsymbol{\theta}) = \max_{X}\{\mathbf{P'Y} - \mathbf{W'X}\colon Y \in Y(\mathbf{X}, \boldsymbol{\theta}, N, T_{\mathrm{D}})\} \text{ (dryland)}. \quad (2)$$

Note that the indirect profit function for dryland does not include an irrigation cost. The profit maximizing farm operator installs irrigation infrastructure when the quasi-rent under irrigation exceeds the quasi-rent under dryland farming, $\Pi_{\mathrm{I}}(\mathbf{P}, \mathbf{W}, \omega, N, \boldsymbol{\theta}) > \Pi_{\mathrm{D}}(\mathbf{P}, \mathbf{W}, N, \boldsymbol{\theta})$.

Appending random error terms, representing unobserved variables that influence profits under both dryland and irrigated regimes, to the profit functions in (2) yields stochastic functions. Let ε_{I} and ε_{D} denote additive, random and independent errors for irrigated and dryland farming, respectively. The farm operator now faces a probabilistic choice and adopts irrigation when

$$\Pi_{\mathrm{I}}(\mathbf{P}, \mathbf{W}, \omega, N, \boldsymbol{\theta}) + \varepsilon_{\mathrm{I}} > \Pi_{\mathrm{D}}(\mathbf{P}, \mathbf{W}, N, \boldsymbol{\theta}) + \varepsilon_{\mathrm{D}}. \quad (3)$$

If we define P_{I} as the probability of observing irrigation, $T = T_{\mathrm{I}}$, then we can then write the probability of choosing irrigation as,

$$\begin{aligned} P_{\mathrm{I}}(T = T_{\mathrm{I}} \mid \mathbf{P}, \mathbf{W}, \omega, N, \boldsymbol{\theta}) = \text{Prob}\,[&\Pi_{\mathrm{I}}(\mathbf{P}, \mathbf{W}, \omega, N, \boldsymbol{\theta}) \\ &- \Pi_{\mathrm{D}}(\mathbf{P}, \mathbf{W}, N, \boldsymbol{\theta}) > \varepsilon_{\mathrm{D}} - \varepsilon_{\mathrm{I}}]. \end{aligned} \quad (4)$$

To estimate the irrigation adoption probability in (4) we must choose a functional form for the profit functions and probability distributions for the error terms. Let the profit functions be represented by first-order Taylor series expansions,

$$\begin{aligned} \Pi_{\mathrm{I}}(\mathbf{P}, \mathbf{W}, \omega, N, \boldsymbol{\theta}) + \varepsilon_{\mathrm{I}} &= \beta_{\mathrm{I0}} + \beta'_{\mathrm{I1}}\mathbf{P} + \beta'_{\mathrm{I2}}\mathbf{W} + \beta_{\mathrm{I3}}\, N + \beta'_{\mathrm{I4}}\boldsymbol{\theta} - \beta_{\mathrm{I5}}\omega + \varepsilon_{\mathrm{I}} \\ &= \beta'\mathbf{Z} - \beta_{\mathrm{I5}}\omega + \varepsilon_{\mathrm{I}}, \quad \text{and} \qquad (5) \\ \Pi_{\mathrm{D}}(\mathbf{P}, \mathbf{W}, N, \boldsymbol{\theta}) + \varepsilon_{\mathrm{D}} &= \beta_{\mathrm{D0}} + \beta'_{\mathrm{D1}}\mathbf{P} + \beta'_{\mathrm{D2}}\mathbf{W} + \beta_{\mathrm{D3}}\, N + \beta'_{\mathrm{D4}}\boldsymbol{\theta} + \varepsilon_{\mathrm{D}} \\ &= \beta'\mathbf{Z} + \varepsilon_{\mathrm{D}}, \end{aligned}$$

where the β's are parameters of the indirect profit functions and $\mathbf{Z}$ is a vector of all independent variables except the irrigation capital cost, ω. Combining Equations (4) and (5) the probability of installing irrigation capacity is,

$$P_{\mathrm{I}}(T = T_{\mathrm{I}}|\mathbf{Z}) = \text{Prob}\,[(\beta_{\mathrm{I0}} - \beta_{\mathrm{D0}} - \beta_{\mathrm{I5}}\omega) + (\beta_{\mathrm{I}} - \beta_{\mathrm{D}})'\mathbf{Z} > \varepsilon_{\mathrm{D}} - \varepsilon_{\mathrm{I}}]. \quad (6)$$

To estimate the model parameters, $(\beta_{\mathrm{I}} - \beta_{\mathrm{D}})$, using a probit model (Long, 1998) let $y_{\mathrm{i}} = 1$ if the ith farm has irrigation capacity and zero otherwise, and let the difference in errors assume a cumulative normal distribution, F.[3] The probability of irrigation, then, is

$$P_{\mathrm{I}}(T = T_{\mathrm{I}}|\mathbf{Z}) = F[(\beta_{\mathrm{I}} - \beta_{\mathrm{D}})'\mathbf{Z}]. \quad (7)$$

If the observations are independent, the likelihood function for estimating the parameters is,

$$L[(\beta_I - \beta_D)|T, \mathbf{Z}] = \prod_{y=1} F[(\beta_I - \beta_D)'\mathbf{Z}] \prod_{y=0} \{1 - F[(\beta_I - \beta_D)'\mathbf{Z}]\}, \tag{8}$$

where the product index indicates the products are taken only over those observations where $y = 1$ or $y = 0$.

This formal specification of irrigation adoption has the advantage of permitting both input and output substitutions. Producers can respond to changing conditions by adopting different technologies, altering the crop mix or letting land lie fallow. However, the model does not capture the full range of adaptations to climate change. Land is fixed, preventing agricultural land from expanding or transferring to non-agricultural uses. Clearly, this is a drawback in terms of simulating a long-run climate change scenario. Nonetheless, the model and empirical specification described below capture the importance of climate extremes and the production adaptations that are likely to occur in response to global climate change.

3. Data and Empirical Application

We employ a probit model (Equation (8)) to estimate the probability of adopting irrigation as a function of expected input prices, **W**, output prices, **P**, the total land available, N, and a vector of physical characteristics that includes measures of climatic variance. The empirical analysis combines survey-based data from individual farm operations with spatially derived (GIS) climatic and soils information that is also unique to each farm location. The climate and soils variables were constructed by applying a GIS-based, non-parametric regression-smoothing technique to create a virtual national "surface" for each variable (Whittaker and Scott, 1999).

In developing our geographic surfaces, the US is partitioned into 10-km^2 cells. To estimate the climate and soil values for each cell, we apply a non-parametric kernel estimating technique developed specifically for spatial climate and weather characterization described in Ali (1998).[4] The resulting climatic and soils surfaces overlaid the geo-referenced farm data, and the relevant variables from the climate and soils surfaces were linked to each farm location. This method improves accuracy of climate conditions relative to past studies using regional average data (see Feather et al., 1999, for another application of this technique).

A brief example will help clarify the procedure. A non-parametric regression procedure was used to develop a national maximum May temperature surface based on monthly summaries from the 5700 weather stations. The maximum May temperature data was then extracted from the surface at each of the 3087 farm locations using the farm latitude and longitude data from the Agricultural Resource Management Survey (ARMS). This procedure allows each farm in the data set to have unique climatic and soils data based on relative location to surrounding weather recording stations and soil survey locations. The appendix describes the data sources and variable definitions in greater detail.

3.1. FARM DATA

Data for individual farm operations is based on the ARMS survey, which is USDA's primary data collection instrument for studying farm resource use (Economic Research Service, 1996). The survey is comprised of several versions adapted to serve different objectives, including commodity versions that collect resource use and other on-farm information about production of specific commodities. We combined the 1996 corn commodity survey with the 1997 soybean and cotton surveys to form a cross-sectional database of 3087 observations. [5] The data cover the major crop production areas for the three crops and include observations in 24 states with greatest coverage in the southern and central portion of the nation. The ARMS provides data for several variables critical to the analysis, including the dependent variable identifying the use of irrigation as a production practice on the farm and several independent variables relating to farm and producer characteristics. The locations of farms in the ARMS survey program are geo-referenced, providing the latitude and longitude references necessary to match geo-referenced climatic and soils variables.

3.2. CLIMATE DATA AND SPECIFICATION

The National Climatic Data Center (NCDC) collects US weather data that make it possible to construct variables that capture climatic variance and the likelihood of extreme events. The climate variables were constructed from variables included in the NCDC, Summary of the Month data series[6] (NCDC, 1997). The climatic variables in the summary of the month series are based on 5700 geo-referenced weather stations that maintained continuous daily temperature and precipitation records for the 30-year period from 1966 to 1995. From those 30 years of monthly summaries, we constructed several temperature and precipitation measures that provide station-specific climatic variables.

Although monthly averages wash out daily extremes, the Summary of the Month data series includes three variables that are effective measures for the tails of the temperature and precipitation distributions and are highly correlated with the frequency of extreme events. For temperature, the number of days in the month exceeding 90 °F captures the upper tail of the daily maximum temperature distribution. Moreover, days greater than 90 °F is a good approximation for the incidence of more extreme heat since its correlation with even hotter events is greater than the mean. For precipitation, Summary of the Month data include, in addition to total monthly precipitation, two useful measures of the precipitation distribution – the number of days in the month when precipitation exceeds 0.1 inch and the number of days when precipitation exceeds 1 inch. The first variable measures the frequency of "effective" rainfall.[7] Days with less than 0.1 inch of precipitation is a good approximation for the duration and severity of drought conditions. Like "days greater than 90 degrees," the "precipitation days greater than one inch" variable measures the upper tail of precipitation distribution and is highly correlated with more excessive precipitation.

In this study, we capture climatic variance by measuring the incidence of climatic events in the upper tails of the climatic distributions using temperature and precipitation thresholds available in published climate data (i.e., days greater than 90 °F and days greater than 1 inch of rainfall). While these thresholds capture the variance of the climate distributions, they do not capture the risk and frequency of more severe events in the extreme tails. To the extent that such extreme events have a differential impact on production decisions, this data limitation constitutes a shortcoming of this study. Data on the incidence of more extreme climatic events would make it possible to discern the climate effects of events higher in climate distributions using the approach developed here.

Multicollinearity was a concern in constructing the climate variables. Daily mean maximum temperatures are correlated with both days exceeding 90 °F and daily minimum temperatures. Total precipitation is correlated with days exceeding 1 inch and days exceeding 0.1 inch Moreover, temperature and precipitation are themselves correlated. High levels of multicollinearity inflate the standard errors, making it difficult to identify significant effects on individual variables. After some experimentation, the final specification mitigated multicollinearity while preserving measures of mean and extreme climate through suitable transformations of the climate variables described below. Despite the multicollinearity, the results show that climate variables associated with the upper tails of the climate distributions are robustly significant.

Although temperature and precipitation have differential impacts on production over the course of the growing season, the estimation could not support monthly climate variables since correlation across months was excessive.[8] Therefore, the climate variables represent the conditions that prevail during the peak of the growing season, June through August.[9]

The irrigation and land allocation decisions are made concurrently and prior to the growing season based on the expected growing-season weather. The independent variables for temperature include: (a) the mean daily maximum temperature for the growing season in °F, and (b) the total number of days over the June-to-August growing period when the temperature exceeds 90 °F.[10] Recent evidence suggests that global warming may manifest in higher nighttime temperatures (Rosenzweig et al., 2000). Thus, the specification also includes a variable to reflect mean daily minimum temperatures. Since mean maximum and minimum temperatures are highly correlated, to mitigate collinearity, this variable is defined as the difference between the average maximum and minimum temperature.

Three variables capture the climatic precipitation conditions facing producers. First, the variable approximating precipitation frequency is the number of days in the June-to-August growing season when precipitation equaled or exceeded 0.1 inch. The second variable corresponds to the mean of the precipitation probability distribution and is computed as the sum of growing-season precipitation (in inches) divided by the number of days with more than 0.1 inch. The third variable, the share of days in the growing season when precipitation exceeds 1 inch, is a proxy for heavy rainfall events. It is computed as the number of days with at least 1 inch of precipitation divided by the number of days with precipitation greater than 0.1 inch. Using the share of days rather than the number of days reduced the collinearity with other measures of climate. Note that days with precipitation exceeding 0.1 inch appears in all three variables. When rainfall frequency increases, holding total rainfall constant, the mean rainfall and the share of days with excessive rainfall both decrease.

We also included two interaction terms that were proposed in the literature – a temperature–precipitation interaction and a precipitation–soil type interaction. Dalton (1997) shows that the correlation between precipitation and temperature is an important determinant of welfare effects of climate on agriculture. High temperatures can be either harmful or beneficial to yield depending on the availability of soil moisture (Runge, 1968). High temperatures with ample soil moisture can boost yields, while heat in the absence of precipitation can reduce yields. The temperature–precipitation interaction term is defined as the total growing season precipitation times the mean maximum temperature. There is also an important interaction between precipitation and soil type (Mearns et al., 1996). Soil characteristics determine the water-intake rate through the soil profile and the ability of soil to retain moisture. The soil–precipitation interaction term is defined as the growing season precipitation times a measure of the topsoil permeability rate.

3.3. PRICES AND WATER AVAILABILITY

Commodity prices were omitted from the analysis because cross-sectional variations in crop prices were, by and large, trivial. Prices for most crop commodities reflect national markets, with transportation costs driving any regional differences. Input prices for farm labor, energy, and nitrogen fertilizer exhibited sufficient regional variation to be included in the analysis. With the exception of irrigation water price, theory does not dictate the signs of the input and output price variables.

The price of water is an important determinant of irrigation adoption. However, creating a good proxy for the marginal opportunity cost of water is problematic for two reasons. First, although the ARMS survey solicited water cost from respondents, it did so only for irrigated farms, not for non-irrigators. Second, several empirical articles in the literature confirm that surface water is not a price-rationed commodity (Moore and Dinar, 1995; Economic Research Service, 2003; Kanazawa, 1993). Institutionally based quantity constraints, historical practice and long-term subsidized contracts govern the allocation of surface water, not prices and markets. States or federal agencies administer water rights and set fees without regard to the relative scarcity of water. This institutional setting implies that on-farm water costs do not reflect the opportunity cost of water nor do water costs govern farmer behavior at the margin. Thus, we opted for a variable that would proxy for the availability of supplemental water.

Because surface water is not price-rationed and groundwater constitutes the primary source of incremental water, we employed a proxy for the availability of groundwater to the farmer. Where groundwater was readily accessible, the shadow price of water would be low compared to areas where groundwater was scarce. From the USGS data (Solley et al., 1998) we constructed a variable defined as the share of total agricultural water in the county derived from groundwater sources. A large groundwater share would indicate the availability of supplemental water and, thus, a lower shadow price. A small share, on the other hand, would indicate the scarcity of marginal water supplies and a higher shadow price.

Finally, note that, in a model that incorporates climate, water price should be endogenous since temperature and precipitation simultaneously affect irrigation demand and fresh water supplies. The estimation of a simultaneous model, however, is beyond the scope of this paper because, without a surface water component, the groundwater share variable is not a good candidate for an instrumental variable approach. Potential simultaneity biases will be addressed in Section 4.

3.4. SOILS AND OTHER DATA

The soil variables are based on cropland soils and topography information contained in the National Resources Inventory (NRI) (Natural Resource Conservation Service, 1999) and state soil survey data. The 800,000 NRI sample points are digitized into a geo-referenced database. The NRI data points link to the soil characteristic data in the STATSGO soil database (Natural Resource Conservation Service, 1995).

Regional dummy variables were also added to capture non-climatic differences in irrigation adoption, such as water laws, institutions, and supporting infrastructure. Four regions were developed based on state boundaries. The east–west line separates the 17 western states where irrigation acreage is concentrated and irrigation institutions are well established. The north–south line was defined somewhat arbitrarily, with the southern region stretching from Virginia through Tennessee to Arizona and California. The division does distinguish the fast-growing areas of irrigation in the south from areas in the Corn Belt and Lake States where irrigation is not as common. More detailed definitions of the variables are in the appendix.

4. Model Results

The likelihood function in Equation (8) was estimated using a maximum likelihood procedure in LIMDEP (Greene, 1998). The estimation included expansion weights

TABLE I
Descriptive statistics and binomial probit estimates

Category	Variable	Sample means	NW means	Coefficient	Standard error	b/SE
Irrigation	irrigation dummy	0.114	0.3	dependent	NA	NA
Region farmsize and prices	Intercept	1.00	1.00	4.88	5.18	0.94
	Northwest dummy	0.14	1.00	0.038	0.324	0.12
	Northeast dummy	0.72	0.00	−0.73	0.364	−1.99
	Southeast dummy	0.10	0.00	0.522	0.259	2.02
	Total acres	641.1	1029.6	1.112E-04	4.04E-05	2.75
	Irrigation energy price	0.08	0.01	1.064	6.34	0.17
	Nitrogen fertilizer price	685.0	98.35	−5.613E-04	2.20E-03	−0.26
	Labor wages	6.72	7.06	0.286	0.147	1.94
Water availability	County groundwater share	0.67	0.73	0.795	0.127	6.25
Precipitation variables	Days > 0.1 inch	18.77	16.91	0.037	0.062	0.60
	Share > 1.0 inch	0.17	0.18	−7.19	2.34	−3.07
	Mean precipitation	0.63	0.63	0.121	1.76	0.07
Interaction terms	Precip*Permeability	1.61	1.38	0.0063	0.015	0.42
	Precipitation*Temp	988.4	913.0	−0.0011	0.001	−1.00
Temperature variables	Mean Max Temp	84.3	85.94	−0.087	0.059	−1.49
	Days > 90	23.90	32.33	0.043	0.012	3.53
	(Max − Min) Temp	11.46	12.37	0.072	0.064	1.120
Soil variables	Soil slope	3.43	3.11	−0.12	0.024	−4.85
	Clay dummy	0.68	0.73	−0.63	0.091	−6.85
	Sand dummy	0.04	0.001	−0.57	0.189	−3.04
Farm and demographic variables	Operator age	51.7	50.1	−0.015	0.003	−5.03
	Op college dummy	0.15	0.18	0.205	0.098	2.10
	Farm primary Occ	0.73	0.80	0.428	0.107	3.98
	> $10K Livestock inventory	0.30	0.41	0.081	0.086	0.950

[a]Complete variable definitions are in the appendix. Probit estimates are distributed asymptotically normal (Long, 1998).

provided with the ARMS data that generate estimates that are representative of US corn, soybean, and cotton farmers. The model correctly predicts the actual outcome – the presence or absence of irrigation – in 86.6% of the observations.

Table I shows, in the first two columns, the variable names and a brief description. Columns 3 and 4 show sample means for the entire sample and the sub-sample of farms in the northwest (states are defined in the appendix). Northwest regional means will be used to simulate changes in the temperature and precipitation distributions in Section 5.[11] The last three columns of Table I show maximum likelihood parameter estimates, standard errors, and t-ratios. With large samples, as is the case here, maximum likelihood estimators are distributed asymptotically normal (Long, 1998).

4.1. CLIMATIC VARIABLES

As Table I shows, the temperature and precipitation distribution effects are captured in eight independent variables. Examining the signs and significance of individual climate coefficients is incompatible with this approach since the estimation includes variables that simultaneously capture the means and tails of the distributions, interactions between temperature and precipitation, and interactions between soil permeability and precipitation. For example, a change in the mean temperature that shifts the temperature distribution toward higher temperatures affects four variables – mean maximum temperature, days greater than 90 °F, day–night temperature difference, and the temperature–precipitation interaction. Increasing the mean maximum temperature without increasing the days exceeding 90 °F is equivalent to decreasing the temperature variance to hold the upper tail of the distribution constant. Rather than report marginal effects at the means of the independent variables, it is more instructive to compute changes in the predicted probabilities for plausible climate change scenarios. The next section illustrates the impact of six climate change scenarios on irrigation adoption probabilities. Each scenario computes the change in predicted probability for a hypothetical shift in the climate distributions.

A few general observations are worth nothing at this juncture. First, the two variables that capture the upper tails of the temperature and precipitation distributions, “share of days in excess of one inch of rain” and “days greater than 90 degrees,” were highly significant, but were the only significant climate variables. This result and the scenarios in the next section will show that changes in the climate means without shifting the corresponding distributions does not significantly impact irrigation adoption. The upper tails of the distributions dominate the determination of irrigation probabilities. Second, although several climate coefficients were insignificant, separate likelihood ratio tests of the joint significance of precipitation variables, temperature variables and interaction terms, rejected the hypothesis that the coefficients were jointly equal to zero. Finally, the sign on the difference between daytime and nighttime temperatures is positive, though not quite significant at the 10% level. Nonetheless, it is worthwhile to provide a plausible interpretation for the positive relationship. Day–night temperature difference is a good proxy for humidity. Humid areas have a smaller day–night temperature difference than non-humid areas. The positive sign suggests that areas with low humidity (i.e., large difference between mean high and low temperatures) are more likely to irrigate.

4.2. WATER AVAILABILITY

Even though the share of total agricultural water derived from ground water sources is only a rough proxy for water availability and price, the proxy variable is positive and highly significant. It is no surprise the availability of water plays such a key role in determining irrigation adoption. Indeed, the ability of producers to use irrigation as a climate adaptation will be significantly constrained by water availability. Public policies that promote more efficient water allocation could facilitate irrigation as an adaptive measure to climate change.

As we noted earlier, we estimated the probit model treating water availability as exogenous. To the extent that the climate variables are correlated with the water price, or its groundwater share proxy, they are subject to simultaneity bias. The simultaneity and expected correlations between temperature, precipitation and water price suggest that the model may overestimate climate effects. For example, the negative impact of higher precipitation on irrigation adoption may be partially offset by lower water prices as increased rainfall augments water supplies.

4.3. NON-CLIMATE VARIABLES

Soil and slope variables were generally significant, with the expected signs. The variable for soil slope is negative and highly significant. That is, greater soil slope decreases the probability of irrigation since high irrigation efficiencies require uniform soil moisture. Where soil slope is excessive, irrigation results in uneven moisture penetration – with insufficient penetration at the head of the field and excess water runoff at the base. The problem is most critical for gravity-flow systems, but is also a concern for pressurized distribution systems.

The soil content results suggest that irrigation is less likely to occur on 'extreme' soil categories and most likely to be adopted on medium-grained, loamy soils. These results are consistent with other empirical studies (see, for example, Negri and Brooks, 1990) showing the major role that soil characteristics play in determining irrigation and irrigation technology. The dummy variable indicating the presence of high clay content is negatively related to the probability of irrigation and is highly significant. The greater the clay content of the soil, the lower the probability of irrigation, since clay soils retain more soil moisture, and irrigation on soils with slow water penetration impose additional challenges. At the other extreme of soil permeability, soils high in sand content also significantly decrease irrigation probabilities. While heavier clay soils lessen the need for irrigation, irrigation efficiencies are often lower or capital requirements significantly increased on high-intake sandy soils – increasing irrigation requirements to meet crop needs.

The variable for total farm acres was positive and significant at the 1% level, suggesting that large farms are more likely to irrigate. This finding is consistent with intuition and is well documented in the literature (Natural Agricultural Statistics

Service, 1999). Larger farms are more highly capitalized, and thus, are more readily able to assume the high up-front capital costs of irrigation system adoption.

The positive and marginally significant coefficient on wages suggests that labor and irrigation are substitute inputs. The prices of irrigation energy per foot of lift and nitrogen fertilizer price were insignificant in the model. The failure of these price variables to have explanatory power may be attributable to the fact that geographic variation in energy and fertilizer costs were not sufficient to capture price effects.[12]

Regional dummies were specified to capture structural differences in the agricultural sector that are independent of climate, such as water laws and institutions, regional input and output markets and regional production history. The results show that the northeast dummy is negative and significant at the 10% level while the southeast and northwest dummies are both insignificant.

With the exception of the dummy variable indicating a major livestock production enterprise on the farm, demographic variables were robust and consistent with expectations. Irrigation requires more capital investment, more expertise, and more management. The variable for operator age was negative and highly significant. Younger operators tend to be more likely to adopt irrigation technology. The dummy variable indicating the farm operator attended college was positive and highly significant. Irrigation requires increased management skills, and education is a good proxy for management capacity. The dummy variable indicating that farming was the operator's primary occupation was positive and significant. Part-time farmers are less likely to incur the capital costs and management demands of an irrigated production system. Finally, the dummy variable for farms with greater than \$10,000 in livestock inventory distinguishes producers who are predominately crop farmers from those who also have significant livestock enterprises. This variable was not significantly different from zero.

5. Simulating Alternative Climatic Conditions

The estimated model can be used to simulate the impact of changes in the probability distributions of both temperature and precipitation on the likelihood of on-farm irrigation. Assuming daily maximum temperature takes on a normal distribution (Katz and Brown, 1992) and precipitation takes on a Weibull distribution (Duan et al., 1988), measures of the upper tail of the precipitation and temperature distribution can be used to calibrate the temperature and precipitation distributions. The probability of temperature exceeding 90 °F can be approximated by the share of days in the period exceeding 90 °F. For example, at the global means of the sample data (see Table I), the mean maximum temperature in the June-to-August growing season is 84.27 and the number of days exceeding 90 °F is 23.9. The daily temperature variance can be constructed by assuming temperature is normally distributed and calculating the variance implied by the upper-tail probability (Figure 1). In this example, the probability that daily temperature exceeds

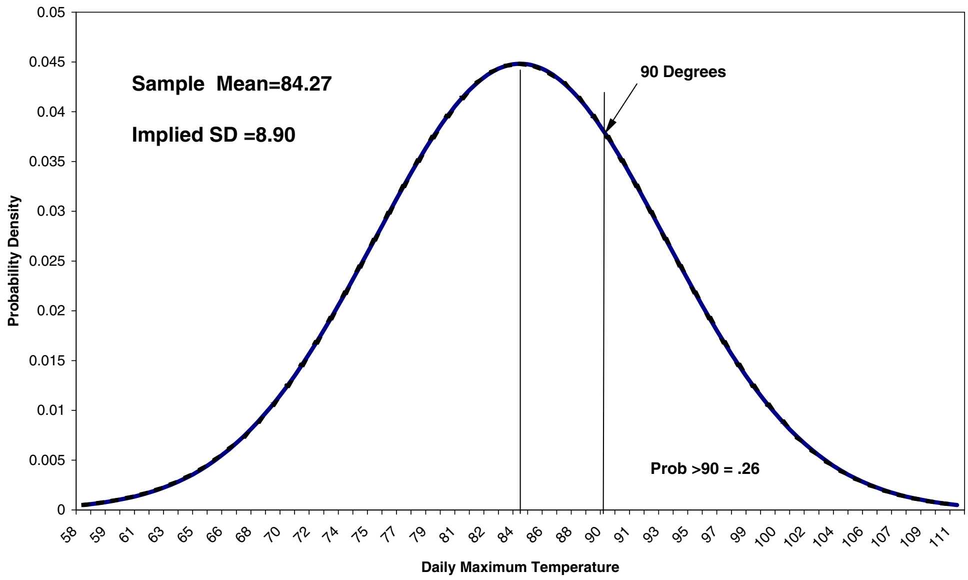

Figure 1. Maximum temperature distribution at sample mean.

90 °F is 0.26 (23.9 days greater than 90 °F divided by 92 days in the growing-season period). The implied standard deviation for the normal distribution is 8.90.

Armed with a parameterization of the temperature distribution and estimates of the impact of climate means and extremes on irrigation adoption, the model can simulate the independent effects of the first two moments of the distribution – changes in the mean holding variance constant and changes in the variance holding mean constant. Note that increasing the mean, holding variance constant, shifts the entire distribution toward warmer temperatures, thereby increasing the frequency of extreme temperatures. Using the distribution in Figure 1, a 3 °F increase in mean temperature, holding variance constant, increases the growing-season days exceeding 90 °F by 11.0 days, from 23.9 to 34.9.

The model can similarly be used to examine the independent effects of changes in the mean and frequency of precipitation and the shape of the distribution. Following the temperature distribution example, we assumed a two-parameter Weibull distribution for precipitation (Duan et al., 1988) and estimated its parameters using mean rainfall and the share of days exceeding 1 inch as an estimate of the probability in the upper tail.[13] At the global means of the sample data, there are 18.8 days of rainfall greater than 0.1 inch in the June-to-August period. The "mean" rainfall, 0.63 inch, is calculated as the average of total precipitation in the period divided by the number of days where rainfall exceeds 0.1 inch of the 18.8 days greater than 0.1 inch, 17% or 3.2 days exceed 1 inch of precipitation. Figure 2 shows the inverse of the cumulative distribution function[14] implied by the mean and upper tail at the global sample mean.

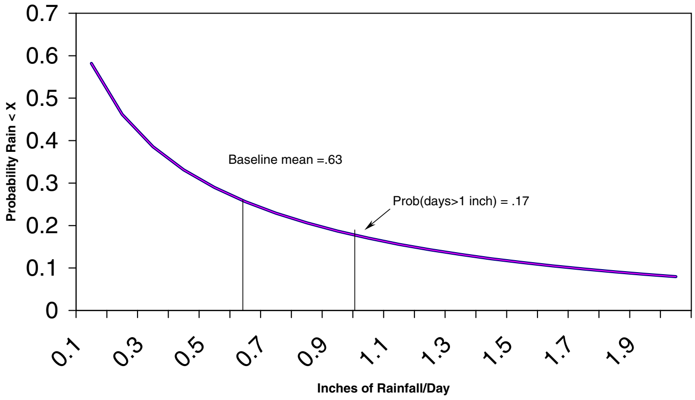

Figure 2. Weibull distribution of precipitation.

An increase in total rainfall, holding the frequency of rainfall constant, will shift the entire distribution to the right, increasing the frequency of extreme rainfall. An increase in rainfall frequency, holding total rainfall constant (i.e., more days with less rain per day), will shift the entire rainfall distribution to the left, reducing mean and extreme precipitation. Changing the shape parameter of the Weibull distribution alters the rainfall distribution, shifting the distribution between light and heavy rain, holding total rainfall and frequency constant. The model can predict the impact on the dependent variable of all of these perturbations.

Since the change in the irrigation probability for a given change in the independent variables depends on the levels of all independent variables, the scenarios evaluate the irrigation probabilities at the sample mean values for the northwest, one of the four geographic regions. Table I shows the sample mean values for the independent variables in the northwest. At the northwest sample means, the model predicts the probability of irrigation is 0.25. The six scenarios report the change in irrigation probabilities compared to the predicted probability at the northwest sample means.

5.1. SCENARIO 1: INCREASE IN TOTAL PRECIPITATION, HOLDING FREQUENCY CONSTANT

In Scenario 1, the total precipitation increases 10%, or 1.06 inch, holding precipitation frequency constant. Figure 3 shows how a 10% increase in precipitation shifts the distribution to the right, increasing mean rainfall from 0.63 to 0.69 and the frequency of precipitation greater than 1 inch from 3.13 to 3.44 days in the June-to-August growing season. The model predicts a 0.066 decrease in irrigation probability compared to the base case since increased soil moisture reduces the need for irrigation. The result is consistent with the expectation that more rainfall reduces the need for irrigation.

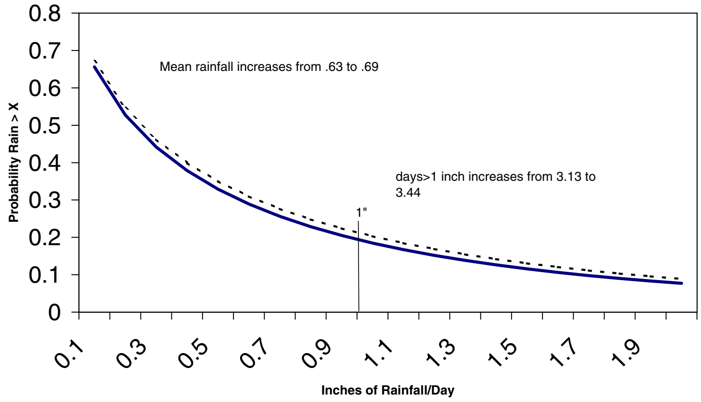

Figure 3. Total rainfall increases 10% or 1.06 inch

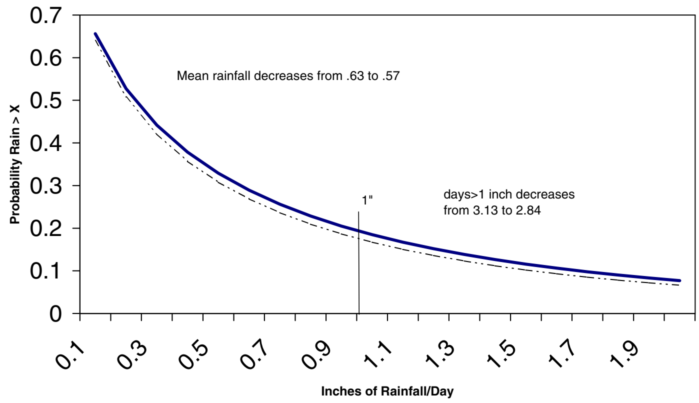

Figure 4. Rainfall frequency increases 1.69 days or 10%.

5.2. SCENARIO 2: INCREASE IN PRECIPITATION FREQUENCY, HOLDING TOTAL RAINFALL CONSTANT

Scenario 2 demonstrates that the relationship between irrigation and precipitation is complex and multidimensional. Figure 4 shows a 10%, or 1.69 days, increase in the frequency of rainfall in excess of 0.1 inch, holding the total rainfall constant. In this scenario, the same amount of rainfall is spread over 1.69 more days, shifting the entire probability distribution to the left. The mean rainfall declines from 0.63 to 0.57 inch in the June-to-August growing period and the days greater than 1 inch also falls from 3.13 to 2.84. The model predicts a 0.10 increase in irrigation probability. It follows that an increase in the number of days of rainfall, holding total precipitation constant, increases the likelihood of irrigation since less effective rainfall is available for crop development. The same amount of precipitation delivered over more days reduces the moisture available for growth as more moisture evaporates before infiltrating the soil. Scenario 2 underscores

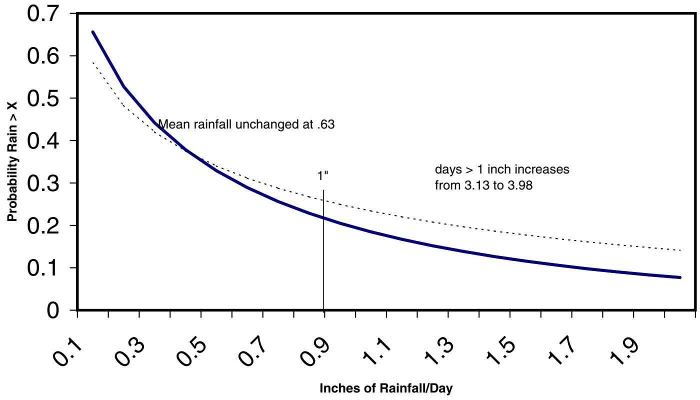

Figure 5. Skew distribution toward heavier rainfall holding total and frequency constant.

the importance of the daily distribution of rainfall, independent of the total precipitation.

5.3. SCENARIO 3: SKEW THE PRECIPITATION DISTRIBUTION TOWARD HEAVY RAINFALL, HOLDING FREQUENCY AND TOTAL RAINFALL CONSTANT

Figure 5 skews the precipitation distribution toward more heavy rainfall holding total precipitation and frequency constant. Skewing the distribution increases the occurrence of large rainfalls while decreasing the occurrence of low rainfalls so as to hold total rainfall constant. The mean remains constant at 0.63 inch while the number of days in excess of 1 inch increases 1 day from 3.13 to 3.98. The model predicts a substantial decline of 0.10 in irrigation probability, as more of the rainfall is available for plant growth. Light rainfall events provide relatively little effective moisture to the plant, as much of this is lost to evaporation on the plant and soil surface. Heavier rainfall events permit moisture saturation of the crop root zone, reducing the need for irrigation.

The first three scenarios underscore the importance of considering the entire precipitation distribution in models of agricultural production. Scenario 3 establishes the upper tail of the precipitation distribution as a driving force in irrigation adoption since the change in irrigation probability was substantial with no corresponding change in total rainfall or rainfall frequency.[15]

5.4. SCENARIO 4: MEAN DAILY MAXIMUM TEMPERATURE INCREASES 3 °F, HOLDING VARIANCE CONSTANT

Figure 6 shows the mean daily maximum temperature increasing 3 degrees to simulate global warming. This scenario holds the variance constant and increases the mean of the temperature distribution from 85.94 to 88.94. Since the mean temperature was relatively high to begin with, the number of days exceeding 90 °F

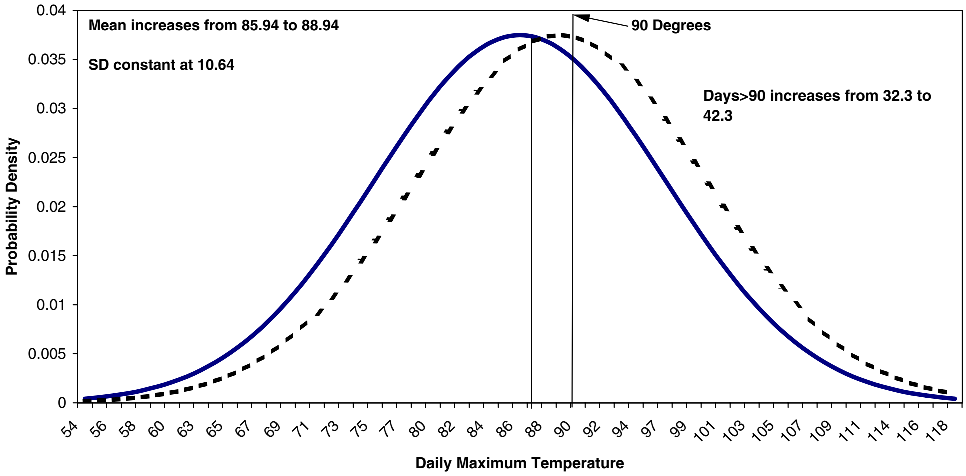

Figure 6. Maximum temperature distribution increases 3 °F.

increases by 10 days, from 32.3 to 42.3. The model predicts a 0.12 increase in the irrigation probability for a 3 °F shift in the temperature distribution.

It is noteworthy that the large increase in the number of days exceeding 90 °F derives from the concentration of probability in the neighborhood of the mean. When the 90 °F threshold is close to the mean, as it is here, its ability to proxy for temperature events in the upper tail of the distribution is significantly diminished. When maximum temperatures are already high, thresholds higher than 90 °F would be more effective in capturing the effects of the temperature distribution.

A modified Scenario 4 illustrates that the driving force behind the temperature effect on irrigation is the upper tail of the temperature distribution, not the mean. Consider a scenario in which we increase the mean temperature and simultaneously decrease the variance so as to hold the upper tail of the temperature distribution unchanged. In other words, the mean increases without increasing the number of 90 °F days. In this hypothetical example, we get the counterintuitive result that irrigation probability marginally declines.[16] Although the small decline in probability may be an artifact of the multicollinearity, model, or estimation, it reveals the dominance of the upper tail in determining irrigation. The effect of the 90 °F days on irrigation adoption overwhelms the small and negative mean temperature effect producing an increase in irrigation corresponding to an increase in temperature.

5.5. SCENARIO 5: INCREASE IN DAILY MAXIMUM TEMPERATURE STANDARD DEVIATION BY 1.06 OR 10%, HOLDING THE MEAN CONSTANT

In Scenario 5 (Figure 7), we hold mean temperature constant and increase the standard deviation by 1.06 °F (10%), from 10.64 to 11.7. Days greater than 90 °F increases only 1.2 days, from 32.3 to 33.5. The reason for the small increase in the

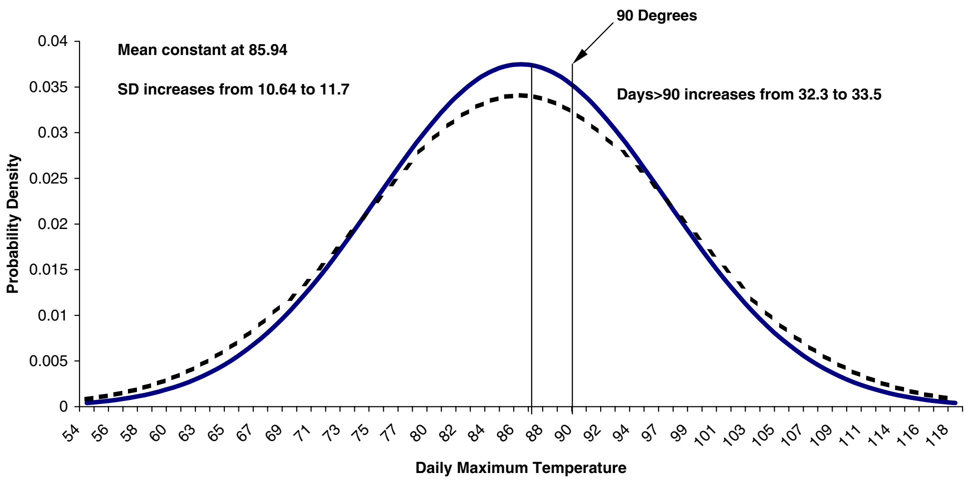

Figure 7. Increase variance of maximum temperature distribution 10% or 1.06 °F.

number of days greater than 90 °F is the same problem we encountered in Scenario 4 – the mean is already too close to the 90 °F threshold. Under these circumstances, increasing the variance will, on the one hand, substantially increase the probability of extreme events and, on the other, not appreciably affect the probability of days in excess of the 90 °F threshold. With a high temperature mean, the 90°F threshold will not adequately capture the irrigation effects of the climatic events in the upper tail. Despite the limitations of the data on temperature, the model predicts a 0.02 increase in irrigation probability. The effect is undoubtedly larger.

5.6. SCENARIO 6: SIMULTANEOUSLY INCREASE MEAN DAILY MAXIMUM TEMPERATURE 3 °F AND DECREASE TOTAL PRECIPITATION 1.06 INCHES OR 10%

Scenario 6 increases mean maximum temperature 3 °F while simultaneously decreasing total precipitation 1.06 inch or 10%. This scenario illustrates the considerable interactive impact of precipitation and temperature. The model predicts a substantial 0.22 increase in the irrigation probability, 5.6% greater than the independent impacts. This scenario predicts a near doubling of the number of irrigated farms in the northwest region. The combination of temperature warming and declining rainfall underscores the potential risk that climate change poses to agriculture, the potential demands climate change places on irrigation, and the importance of modeling the temperature-precipitation interaction.

6. Conclusions

This paper develops a discrete choice model and related variables that capture the effects of both climate means and extremes on the decision to adopt irrigation.

Climatic means and frequencies of climatic events in the upper tails of the temperature and precipitation distributions are used to calibrate the parameters of a normal distribution for temperature and a Weibull distribution for precipitation. Using estimates from a probit model and the parameterized climate distributions, we examine the independent effects of climatic mean and variance on the probability of adopting irrigation. This framework for incorporating the distributions of rainfall and temperature into an empirical economic model of agricultural production can be applied more generally to examine the impact of climate variability and climate change on other agricultural inputs and outputs.

The results show that agricultural adaptation to changing climatic conditions will depend considerably on how climate change affects the distributions of temperature and precipitation. It is no surprise that higher temperatures and less rainfall increase irrigation. What is significant here is that the empirical results show extreme climatic events and biophysical interactions play a crucial role in the decision to adopt irrigation. The tails of the temperature and precipitation distributions are dominant explanatory forces in irrigation and are likely to be important determinants in other production decisions.

Beyond the climatic impacts, the results also show that the ability to employ irrigation as an adaptation to climate change is constrained by water availability, farm size, soil conditions and even operator demographics. As expected, water availability is a primary determinant of presence of irrigation capacity.

Finally, this analysis does not capture the full range of climatic adaptations. In particular, the model holds total land fixed, preventing the long-run transfer of land into or out of agriculture. Moreover, water availability and price should be treated as endogenous as climate simultaneously affects irrigation demand and water supply. Future empirical research on the agricultural impacts of climate change should treat agricultural land and water as endogenous and capture the impact of climate extremes by incorporating measures of the tails of the temperature and precipitation distributions.

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Appendix: Variable Definitions and Data Sources

DEPENDENT VARIABLE

Irrigation is a binary variable on the occurrence of irrigation on the farm in the survey year. It is 1 if irrigation occurred and 0 otherwise, based on the Agricultural Resource Management Survey (ARMS) (Eeconomic Research Service, 1996).

CLIMATIC VARIABLES

Days > 0.1 inch is the number of days in a June-to-August growing season with precipitation totaling 0.1 inch or more. We refer to this as "the days of rainfall" or "rainfall days" even though we do not account for days with only a "trace" of rain.

Share >1.0 inch is the share of days in a June-to-August growing season when precipitation exceeds 1 inch It is computed as the number of days with at least 1 inch of precipitation divided by the number of days with precipitation greater than 0.1 inch. It serves as a measure of rainfall intensity.

Mean Precipitation represents the mean precipitation event in the June-to-August growing season in inches. It is computed as the sum of growing season precipitation divided by the number of days with precipitation greater than 0.1 inch

*Precip*Permeability* is a multiplicative interaction term computed as the sum of June-to-August precipitation (in inches) times soil permeability. Soil permeability is expressed as the average of the maximum and minimum topsoil permeability rate (inches per hour) as reported in the STATSGO soil database (Natural Resource Conservation Service, 1995).

*Precipitation*Temp* is a multiplicative interaction term computed as the sum of June-to-August growing season precipitation (in inches) times the average maximum monthly temperature over the same period (°F).

Mean Max Temp is the average maximum monthly temperature over the June-to-August growing season (°F).

Days > 90 is the total number of days over the June-to-August period when the temperature exceeds 90 °F.

(Max − Min) Temp is the difference between the average maximum monthly temperature and the average minimum monthly temperature over the June-to-August period (°F). It serves as a measure of nighttime cooling which is highly correlated with humidity.

REGIONAL DUMMIES

Northeast is a regional dummy that is 1 if the observation is in the Lake States, Corn Belt or northeast regions, and 0 otherwise.

Northwest is a regional dummy that is 1 if the observation is in the Northern Plains (ND, SD, NE, KS), Northern Mountain (ID, MT, WY, NV, UT, CO), or Northern Pacific (WA, OR) regions, and 0 otherwise.

Southwest is a regional dummy that is 1 if the observation is in the Southern Plains (OK, TX), Southern Mountain (AZ, NM), or Southern Pacific (CA) regions, and 0 otherwise. The omitted dummy in the specification.

Southeast is a regional dummy that is 1 if the observation is in the Delta States (AR, LA, MS), Southeast (AL, GA, SC, FL), or Appalachian (TN, NC, KY, VA, WV) regions, and 0 otherwise.

FARM AND FARMER CHARACTERISTICS

Total Acres is the total acres operated on the farm based on the ARMS survey (Economic Research Service, 1996).

Soil Slope is expressed as the average of the maximum and minimum slope (%), as reported in the STATSGO soil database (NRCS, 1995).

Clay Dummy is a binary variable that is 1 if the surface texture of the soil is rated as "clay like" and 0 otherwise. It includes six soil textures in the STATSGO soil-texture rating scale from sandy clay loam to clay (Natural Research Conservation Service, 1995).

Sand Dummy is a binary variable that is 1 if the surface texture of the soil is rated as "sandy" and 0 otherwise. It includes six soil textures in the STATSGO soil-texture rating scale from coarse sand to loamy sand (Natural Research Conservation Service, 1995).

Operator Age is the age of the principal farm operator in years, from the ARMS (Economic Research Service, 1996).

Op College Dummy is a binary variable representing the formal education level of the primary operator, 1 if attended or graduated from college and 0 if formal education stopped at or before completion of high school as recorded by the ARMS (Economic Research Service, 1996).

Farm Primary Occ is a binary variable representing the primary occupation of the principal farm operator, 1 if a full-time farm operator and 0 if a part-time operator as recorded by the ARMS (Economic Research Service, 1996).

>$10K Livestock Inventory is a binary variable that is 1 if the farm had more than $10,000 in current livestock inventory at the time of the survey and 0 otherwise, as recorded by the ARMS (Economic Research Services, 1996).

INPUT PRICES

Groundwater Share is the county share of freshwater irrigation withdrawals from groundwater relative to the total county freshwater irrigation withdrawals in 1995 (Solley et al., 1998).

Irrigation Energy Price represents the unit energy cost of providing irrigation water. This variable is based on energy costs for pumping (dollars per acre-foot of lift). Irrigation energy costs were computed at the state level, using price-updated data from the Farm and Ranch Irrigation Survey (Bureau of the Census, 1996).

Nitrogen Fertilizer Price represents the unit cost of nitrogen fertilizer (dollars per ton for ammonium nitrate (National Agricultural Statistics Service, 1998a)) for a region.

Agricultural Labor Wage is the hourly field-labor wage rate (National Agricultural Statistics Service, 1997, National Agricultural Statistics Service 1998b).

Notes

[1]See Schimmelpfennig (1996) for a survey of a few other studies that incorporate some degree of climatic variance.

[2]In the intermediate run, land is often available in fixed amounts.

[3]The adoption probability can also be estimated using a logistic model. Long (1998) details the differences in the two approaches.

[4]Ali (1998) defines bandwidth as the radius defining the boundary for inclusion of weather station data in estimation of the cell values. In estimating climate and soil variables for each cell, bandwidth is a function of the density of stations in the neighborhood of the geographic cell and is constructed such that the estimate includes at least four weather stations. The largest bandwidth used in the construction of the surfaces is 95 km or about 60 miles.

[5]This study relies on the whole-farm data collected in Phase III of the survey to determine if irrigation was used anywhere on the farm. See Economic Research Service (1996) for details on the differences in alternative phases of the survey.

[6]The Southern Regional Climate Center, Baton Rouge LA, processed 30 years of monthly data into climatic averages for each weather station.

[7]We assume that days of rainfall less than 0.1 inch do not contribute enough soil moisture to affect irrigation decisions.

[8]To an extent climate in distinct periods of the growing season or outside the growing season differentially impacts the irrigation decision, omitting these variables constitutes a source of bias.

[9]In several preliminary estimations, we included a preseason rainfall variable because it may influence the irrigation decision by contributing to soil moisture early in the growing season. The inclusion of preseason rainfall did not substantively alter the results.

[10]Temperature thresholds greater than 90 °F are not readily available. A higher temperature threshold would more accurately capture the upper tail of the temperature distribution. The 90 °F temperature level is approaching critical threshold temperature levels for plant development due to heat stress as reported in Rosenzweig, et al. (2000).

[11]Dummy variables for region require region-specific simulations. We chose the northwest region because it illustrated both the strengths and weaknesses of this approach.

[12]Although not significant, the negative coefficient on nitrogen fertilizer suggests it may be a complementary irrigation input. The complementary use of irrigation and fertilizer is plausible because the higher yields associated with irrigation require greater nutrient inputs, especially nitrogen. If irrigation is an important adaptation strategy to climate change, it may entail added green house gas emissions from increased fertilizer use.

[13]The Weibull cumulative density function employed here is $F(x) = 1 - e^{-[\frac{kx}{\lambda}]^c}$, where x is daily precipitation, $\lambda = E(X)$ the expected value of daily precipitation, $k = \Gamma\left(1 + \frac{1}{c}\right)$, where c is the shape parameter and Γ is the Gamma function. Duan et al., (1988) estimate parameters of the Weibull distribution for precipitation $k = 1.191$ and $c = 0.75$. We calibrate the Weibull distribution such that the probability of precipitation greater than 1 inch equals the sample probability ($k = 1.5$ and $c = 0.60$).

[14]Figure 2 shows the inverse of the cumulative distribution function, $1 - F(x)$, where $F(x)$ represents the probability of events less than x.

[15]Rainfall in excess of 1 inch may not capture the irrigation effects of precipitation events higher in the tail, as in the case of torrential rains. The point at which runoff dominates infiltration is a function of permeability, slope texture, state of crop growth and rain intensity. This underscores the complexity of the relationship between production and biophysical conditions.

[16]One would still expect a modest increase in irrigation probability as the skewed temperature distribution would still have a warmer average. But, obviously, the model cannot capture that subtlety.

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